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A GENETIC SEARCH TECHNIQUE FOR IDENTIFICATION OF AIRCRAFT DEPARTURES

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Abstract

Methods of testing aircraft for departures range from simple, single-parameter criteria to complex, in-flight departure resistance maneuvers. These methods are useful for predicting departure characteristics, but single-parameter methods may be limited in accuracy because of simplifying assumptions made in their derivation. Also, in-flight or simulation testing of departure resistance maneuvers can be limited by the small number of conditions tested. These limitations increase at high angles of attack where the dynamics of the aircraft are more complex. This paper presents a method for using genetic algorithms to augment traditional evaluation criteria. Quasi-random control inputs are generated by a genetic algorithm for a high fidelity X-31 simulation. Each input is evaluated to determine if it causes a departure. The result of the genetic-algorithm-based search is a population, or set, of control input combinations that lead to uncontrolled flight conditions in the simulation. Recognizing possible differences and simplifications between simulation models and the real aircraft, the results show that the method used is effective for finding possible departures caused by inertial coupling and aerodynamic asymmetries. Simulation data are used to show the results of the genetic algorithm search.

Nomenclature

$C_{n_{\beta_{dyn}}}$ dynamic directional stability parameter, 1/rad

$C_{n\beta s}$ stability axis directional stability parameter, 1/rad

C_{no} yawing moment coefficient for zero sideslip

Ixx moment of inertia about the aircraft X axis, slug ft^2

Izz moment of inertia about the aircraft Z axis, slug ft^2

Lat Stk lateral stick deflection, %max

$LCDP$ lateral control departure parameter, 1/rad

Long Stk longitudinal stick deflection, %max

M_{ic} inertial coupling-induced pitching moment, $\text{ft} \cdot \text{lb}$

p body axis roll rate, deg/sec

pvv velocity vector roll rate, deg/sec

q body axis pitch rate, deg/sec

r body axis yaw rate, deg/sec

α angle of attack, deg

$\dot{\alpha}$ angle of attack rate, deg/sec

β sideslip angle, deg

$\dot{\beta}$ sideslip rate, deg/sec

ΔC_{no} change in yawing moment coefficient for zero sideslip

Introduction

Departure resistance testing is one of the most difficult tasks to accomplish when testing highly

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nonlinear systems, such as modern fighter aircraft, and presents a challenging problem for system designers. Departure susceptibility has increased as fighters have become more agile.[1] Flight control system designers must make a trade between taking advantage of available control power to achieve maximum agility and ensuring controllability and departure resistance. To insure adequate departure resistance, the aircraft is flown with a margin of safety away from conditions that could invoke departure, reducing the available maneuverability of the aircraft. These boundaries are calculated using several techniques derived to quantify the static and dynamic stability characteristics and the departure resistance of the aircraft.

Some examples of the simple single-parameter criteria most often used to determine the departure resistance characteristics of a design include $C_{n_{\beta_{dyn}}}$ [2], or the dynamic directional stability parameter; *LCDP* [2], or lateral control departure parameter; and $C_{n\beta s}$ [3], or stability axis directional stability parameter. Although these parameters have been established as good prediction methods[4] and offer some insight into the characteristics of a given aircraft, they have not demonstrated consistent correlation with flight test data to be considered totally reliable[3], especially for high-angle-of-attack, α, flight conditions.[5] These criteria involve using simplifying assumptions related to linearization of the equations of motion, which could lead to inaccurate conclusions. Efforts have been made to improve upon these criteria with some success, but control system influences were not taken into account.[3]

To include the flight control system influences, nonlinear simulations are often used to test for aircraft departure susceptibility. Departure resistance is evaluated by simulating highly dynamic maneuvers designed to test the limits of the system. This procedure usually involves the use of a basic set of maneuvers (clinicals)[6], such as spins and rapid inputs. However, these maneuvers cannot completely test the capabilities of the aircraft for every possible flight condition and control input combination. An infinite number of possible input combinations exists.

To augment these simulation tests, an optimization or search technique is needed to locate possible control inputs leading to departed, or uncontrolled, conditions. Optimization could involve maximizing some parameter set, such as a combination of aircraft states, to represent a departed flight condition. This paper describes a method for using genetic algorithms to augment traditional evaluation techniques. Genetic algorithm search techniques represent one example of an optimization technique that can search a solution space in a quasi-random fashion. Such techniques lend themselves well to the application of complex system testing.

Aircraft Description

Figure 1 shows the X-31 Enhanced Fighter Maneuverability demonstrator aircraft. This aircraft was designed to test the poststall portion of the flight envelope for fighter aircraft. One goal of the project was to test the possible tactical and agility benefits available from fully integrated thrust vectoring in the slow speed arena up to 70° angle of attack. The aerodynamics in poststall flight involve very nonlinear effects from vortex shedding and other phenomena, making control of the aircraft in this flight regime difficult. This difficulty is particularly true for precise maneuvers, such as tracking or nose pointing.

The X-31 flight control system was designed using modern control theory with full state feedback. The high degree of complexity of the flight control system and the nonlinear characteristics of poststall flight make testing

Figure 1. The X-31 aircraft.

for departure prone areas of the flight envelope difficult, making the X-31 aircraft an ideal candidate for this study.

Genetic Algorithms

Genetic algorithms are a structured random search technique based on evolutionary programming principles that mimic modern representations of biological evolution. The Darwinian concept of “survival of the fittest” and a structured random information exchange among a population of artificial chromosomes, or binary strings, is used for the search procedure. Genetic algorithms differ from numerical search methods used for optimization for several reasons. First, they work with a coding of the parameter set, not the parameters themselves. Second, they search from a population of possible solutions instead of a single point. Third, they use probabilistic rules of transition instead of deterministic rules. For example, genetic algorithms do not require that first and second derivative data be calculated for the fitness function with respect to the independent variables. The majority of deterministic methods rely on these data to guide the search.

Genetic algorithms require that the parameter set to be optimized be coded into a finite length string. For this example, a search for possible control input combinations leading to a departed flight condition requires that the control inputs be coded into a form the genetic algorithm can operate on. One way of doing this is to represent the control inputs as binary strings of a finite length. Additional details regarding binary conversion of control inputs is provided in the Experimental Method section. An initial set, or population, of a given number of these possible input combinations would form an initial set of inputs to begin the genetic search. These strings are then evaluated using a fitness function, and the resulting value is used to determine which strings, or control input combinations, are operated on by the genetic algorithm.

A population size of 100 input strings was used for this study based on suggestions from reference 7. Genetic algorithms work iteration by iteration, operating on a population of strings. This operation is similar to natural population growth, where each generation successively evolves into the next generation through reproduction. This approach varies greatly from traditional optimization techniques that search from point to point using some deterministic transition rule, such as a gradient. For this discussion, this evolutionary process will be referred to as the genetic process. For simple genetic algorithms, the process is made up of three operators called *selection*, *crossover*, and *mutation*.

Selection evaluates each binary string according to a fitness value. Binary strings with higher fitness values are selected for combination with other superior strings to form a new population. Selection makes sure that the characteristics of strings with the highest fitness values are passed to the next generation. For this study, tournament selection is used to select the strings used to form the new population. Tournament selection allows the best strings to be mated with other superior strings a number of times that is proportionate to fitness value until a new population of strings is formed that equals the total number of strings available in the initial population. More detail on different selection methods is available in reference 7. This reference also provides a good introduction to genetic algorithms.

Crossover is the process by which superior strings are joined together to form a new string and consists of three steps. First, the newly selected strings are paired together at random. Next, an integer position along every pair of strings is selected as the crossover point. Finally, based on a probability of crossover, the paired strings undergo crossover at the integer position along the string. In other words, the first section of one string of the pair is combined with the last section of the other string from the pair and vise-versa. This combining process results in a new pair of strings that shares characteristics of the original pair. The crossover probability of 60 percent used in this study corresponds to 60 percent of the strings being crossed over and 40 percent being left intact. This value is variable and depends on the problem being addressed. Crossover insures that characteristics of the most fit binary strings are passed on to subsequent generations, while still allowing new structures to enter into the search space. Selection and crossover give genetic algorithms most of their search power.[8] The use of this process is the distinguishing characteristic of genetic algorithms.

Next, the population of binary strings that is formed from the selection and crossover process is operated on by mutation. Mutation involves switching individual bits in the string according to a mutation probability value. For instance, a mutation probability of 0.1 would indicate that 10 out of 100 bits in a binary string would be switched. This process introduces random changes into the solution space, reducing the possibility that the genetic algorithm will find a local minimum or maximum instead of the global optimal solution. Mutation also allows the search to include binary strings that may not be found by the crossover process. Mutation is useful to the genetic process, but excessively high mutation probabilities cause the genetic algorithm to represent a random search of the possible solution space. High mutation rates can also destroy the genetic information that is usually passed to the next generation through the crossover process.

After the initial population has undergone all three steps of the genetic process, a new population of strings will exist. The new population is evaluated to find the fitness value for each binary string in the population, and the steps are repeated. Each iteration of the genetic process, including the fitness evaluation, is referred to as one generation. The genetic process is stopped after the average fitness value of the whole population is close to the best fitness value of the best binary string.

Genetic algorithms were originally developed by Holland.[9] They have since been applied to many practical problems relevant to aerospace vehicles.[10–14] Many types of genetic algorithms exist, but only the simple form described here was used in this study. Koza provides an advanced presentation of genetic algorithms and evolutionary programming concepts.[15]

Experimental Method

To test the ability of genetic search techniques to determine control inputs that could lead to departure, a program was written to convert a time history of control inputs into a format that could be manipulated by the genetic algorithm code. Table 1 contains all the possible control input combinations considered for this study and

Table 1. Binary representation possible stick input combinations 5-bit string system.

	Inputs*			
Bit string	Lateral stick, % max	Longitudinal stick, % max	Rudder pedal, %max	Descriptions
00000	0	0	0	No deflection
00001	0	0	0	No deflection
00010	0	0	0	No deflection
00011	0.5	0	0	Half lat stk
00100	0	0.5	0	Half long stk
00101	0	0	0.5	Half rudder
00110	–1	0	0	– Lat stk
00111	1	0	0	Lat stk
01000	0	–1	0	– Long stk
01001	0	1	0	Long stk
01010	0	0	–1	– Rudder
01011	0	0	1	Rudder
01100	–1	–1	0	– Lat stk – Long stk
01101	–1	1	0	– Lat stk + Long stk
01110	1	–1	0	Lat stk – Long stk
01111	1	1	0	Lat stk + Long stk
10000	–1	0	–1	– Lat stk – Rudder

Table 1. Continued.

Bit string	Inputs* Lateral stick, % max	Longitudinal stick, % max	Rudder pedal, %max	Descriptions
10001	–1	0	1	– Lat stk + Rudder
10010	1	0	–1	Lat stk – Rudder
10011	1	0	1	Lat stk + Rudder
10100	0	–1	–1	– Long stk – Rudder
10101	0	–1	1	– Long stk + Rudder
10110	0	1	–1	Long stk – Rudder
10111	0	1	1	Long stk + Rudder
11000	–1	–1	–1	– Lat stk – Long stk – Rudder
11001	–1	–1	1	– Lat stk – Long stk + Rudder
11010	–1	1	–1	– Lat stk + Long stk – Rudder
11011	–1	1	1	– Lat stk + Long stk + Rudder
11100	1	–1	–1	Lat stk – Long stk – Rudder
11101	1	–1	1	Lat stk – Long stk + Rudder
11110	1	1	–1	Lat stk + Long stk – Rudder
11111	1	1	1	Lat stk + Long stk + Rudder

* Scale factor to maximum control input value (i.e. 0.5 = 50 percent stick deflection).

the corresponding binary string value. These strings represent the control input values at a given time point. The controls listed in the table include the longitudinal and lateral stick position and the rudder pedal position. Throttle setting was held at maximum power for all the maneuvers. These 5-bit strings are strung together, one per second, to represent a control input time history. A 1-sec frequency of control inputs was chosen as a starting point for this study. A 1-sec input frequency is high enough to test the controls but still low enough to remain a realistic input frequency for a pilot.

The flight condition used to trim the simulation was also coded into a binary format and was included at the end of each control input string group as an additional 5-bit string. The first two bits in the string represented trim altitude. The last three represented the trim angle of attack. Tables 2 and 3 list the possible trim conditions for the start of the simulation. These flight conditions were chosen arbitrarily with the 55° angle-of-attack trim added to augment aerodynamic asymmetry testing.

Figure 2(a) shows a typical bit string representation for a 5-sec control input and the resulting input signals,

Table 2. Altitudes for trim conditions.

Bit string	Altitude for trim, ft
00	10,000
01	20,000
10	30,000
11	40,000

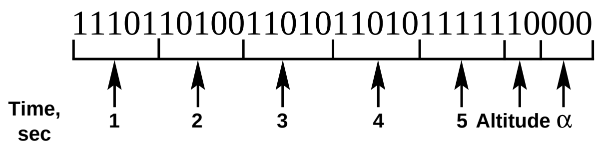
Table 3. Angles of attack for trim conditions.

Bit string	Angles of attack, deg
000	10
001	20
010	30
011	40
100	50
101	55
110	60
111	70

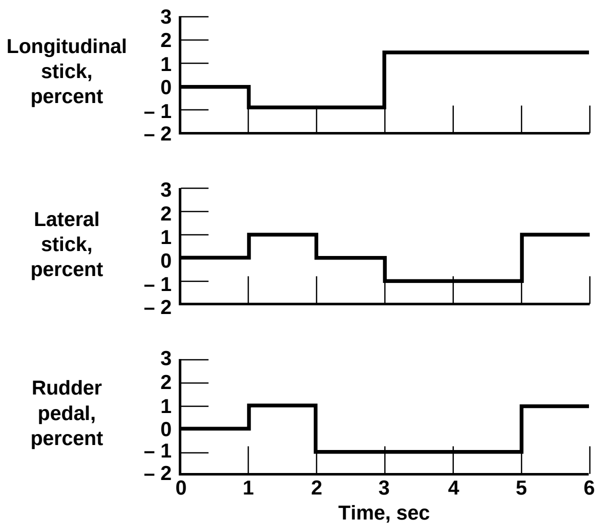
including the trim condition. It consists of 25 bits representing the 5 input strings and 5 additional bits for the trim condition. By including the trim condition as part of the string, different points in the flight envelope are tested for possible departures. The 5-sec input time was chosen after observing that departures for the resulting inputs occurred within the first few seconds of the simulation.

For the simulation of each input, the trim control values are held until the 1-sec point. Then, the inputs from the string are used. The controls are held for the first second of the simulation run to ensure a good trim is held before the start of the maneuver. Also, the last control input value input at the 5-sec point is held for 1 sec, yielding the 6-sec total time length shown in figure 2(b).

To assign a value representing the "level" of departure caused by each possible control input sequence, a fitness function needed to be designed. This function represents a departed flight condition as some numerical combination of the states of the aircraft and is similar to the objective function used in a standard optimization problem. The definition of the fitness function can greatly influence the types of solutions found by the genetic algorithm because it influences which input strings survive and which ones do not. The importance of a well designed fitness function became evident from the results of this study.



(a) Binary string representation of the control inputs. (Controls held at trim value from 0- to 1-sec point of run and held after last input.)



(b) Stick and rudder inputs as a function of time.

Figure 2. Binary string representation of control input and resulting time history.

The initial fitness function was as follows:

$$\text{Fitness}(p, q, r, \beta) = |p| + |q| + |r| + |\beta| \tag{1}$$

where

p	=	body axis roll rate
q	=	body axis pitch rate
r	=	body axis yaw rate
β	=	sideslip

This fitness function was chosen as an initial guess because departures can involve a combination of these parameters. Angle of attack was not included because departures at all angles of attack were of equal interest. The terms were normalized to equally include positive and negative values. Also, the fitness was evaluated at each time step in the simulation, and the maximum value was taken for the whole simulation run. The maximum for the whole was taken, so the simulation could run without any control inputs for a given time segment if doing so would later lead to an increased fitness value.

After the genetic algorithm was run for 100 generations, it was noticed that all the control input combinations in the final population involved full lateral stick inputs held for the entire simulation run. The full lateral inputs caused the fitness values to be dominated by the roll rate term in the fitness function because roll rate in the X-31 flight control system at low angles of attack can be commanded to 240 deg/sec, which is much larger in magnitude than the maximum values of the other terms in the equation. The sensitivity to roll rate indicated a need for a new fitness function that would equally weigh all the terms in the equation because holding constant lateral control input resulted in a trivial maneuver that was not a departure.

Weights were added to the original fitness function, giving roll, yaw, pitch, and sideslip values similar relative magnitudes. This was done to more adequately represent a departed condition in the simulation. Despite changes in maximum available commanded values of these states because of angle of attack in the flight controls, the revised fitness function resulted in more realistic results. The resulting equation is shown below.

$$\text{Fitness}(p, q, r, \beta) = 0.01|p| + 0.1|q| + 0.1|r| + |\beta| \quad (2)$$

Figure 3 shows the best and average values for this fitness for a simulation run of a population of 100 strings for 50 generations. This plot shows how quickly the genetic search technique finds fitness values very close to the best input and drives the average population fitness toward this goal by the genetic process.

Results and Discussion

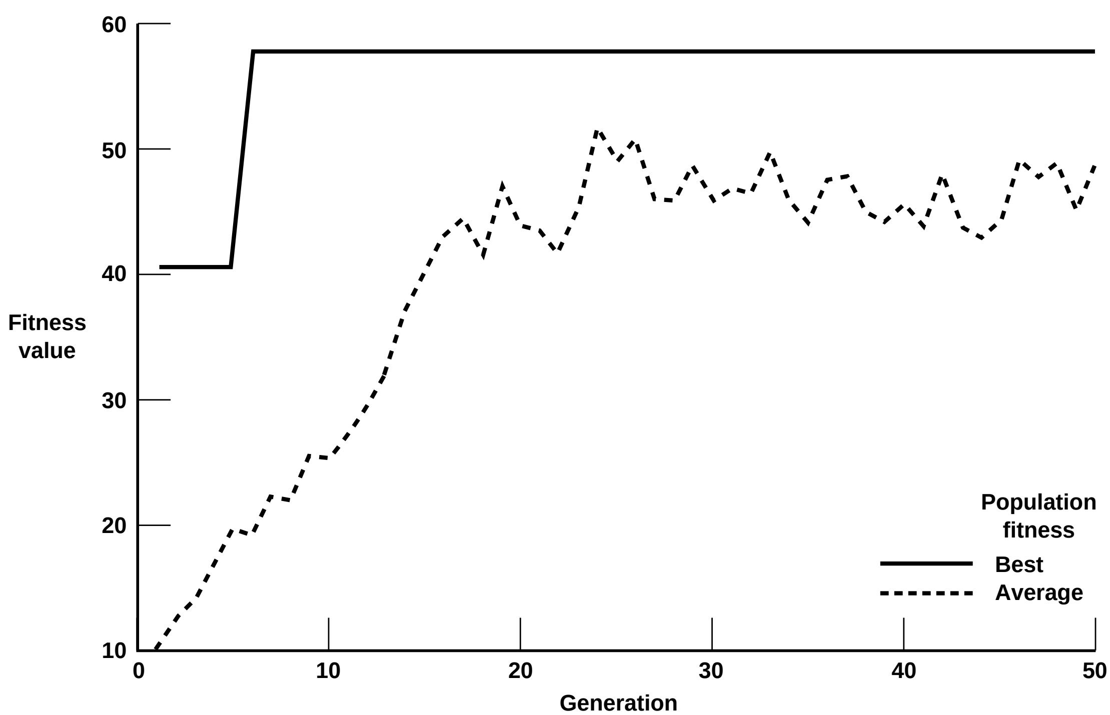
The results of the genetic search are described next. Only the resulting input strings with the best fitness values were evaluated although a whole population of strings exists that could represent other departures at the end of the genetic search. Evaluation of all the strings in the final population is beyond the scope of this study.

Inertial Coupling Departure

The initial results from the genetic investigation of the X-31 simulation led to a departure mode that is consistent with many high-performance fighter aircraft: an inertial coupling departure. The large pitch and yaw inertia as compared to small roll inertia for modern fighters leads to typical inertial coupling problems for high roll rate maneuvers.

To aid in visualizing this effect, the fuselage heavy mass distribution of a fighter is represented as a dumbbell with the mass concentrated at the two ends. As the airplane rolls about the velocity vector, the dumbbell tends to pitch up to align itself perpendicular to the velocity vector roll axis. The resulting pitching moment can be powerful enough to overcome the maximum available nosedown pitch control of the flight controls, resulting in a departure. The pitching moment induced by this effect can be calculated from the following equation:[15]

$$M_{ic} = (Izz - Ixx)pvv^2 \sin 2\alpha \quad (3)$$



F i g u r e 3 . A v e r a

where

M_{ic} = inertial coupling-induced pitching moment

I_{xx} = moment of inertia about the aircraft x axis

I_{zz} = moment of inertia about the aircraft z axis

pvv = velocity vector roll rate

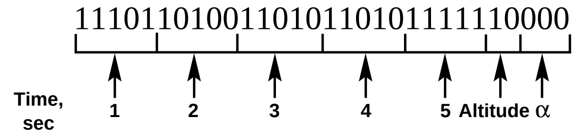
α = angle of attack

This equation shows how high velocity vector roll rates, typical of modern fighter aircraft, can translate into high inertial pitching moments. Similar coupling can also occur in the yaw axis when roll and pitch rates inertially couple to increased yaw rate.[16]

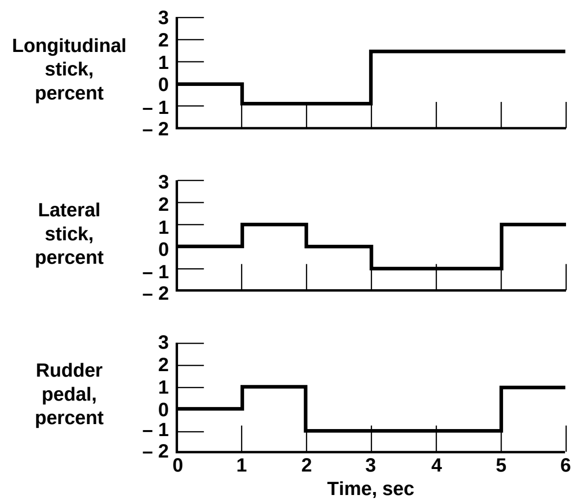
Figures 4, 5, and 6 show the inputs and state time histories for an inertial coupling departure from multiple rolls at low angle of attack coupled with a pitch change. The genetic algorithm search converged on a trim condition of 10° angle of attack at 30,000 ft and the control inputs shown in figure 4. The inputs cause the aircraft to roll at very high rates in both directions at negative angles of attack. As the roll rate increases to the maximum of around –160 deg/sec at approximately 3.5 sec into the run, adverse sideslip increases. This increase indicates that the roll and yaw rates are not coordinated for the velocity vector roll.

After the 3-sec point, the pitch control input commands maximum noseup angle-of-attack rate. This rate leads to an increase in angle of attack that causes an inertial coupling departure after the 5-sec point, as shown by the sudden increase in sideslip, yaw rate, and pitch rate after about 5.5 sec. Figure 7 shows that the canard and trailing-edge surfaces are rate limiting during this departure after about 5.5 sec. In addition, the yaw thrust-vectoring command is position limited, indicating the yaw-vectoring command is unable to command the yaw rate needed to overcome the departure dynamics.

The pitch-up during the departure is in the same direction as commanded angle of attack but reaches a higher value than is commanded by the flight controls. The maximum commanded angle-of-attack rate is 25 deg/sec in the X-31 flight control system, but this series of inputs yields a maximum angle-of-attack rate of over 140 deg/sec at about 6 sec (fig. 8).



(a) Binary string representation of the control inputs. (Controls held at trim value from 0- to 1-sec point of run and held after last input.)



(b) Stick and rudder inputs.

Figure 4. Inertial coupling departure inputs.

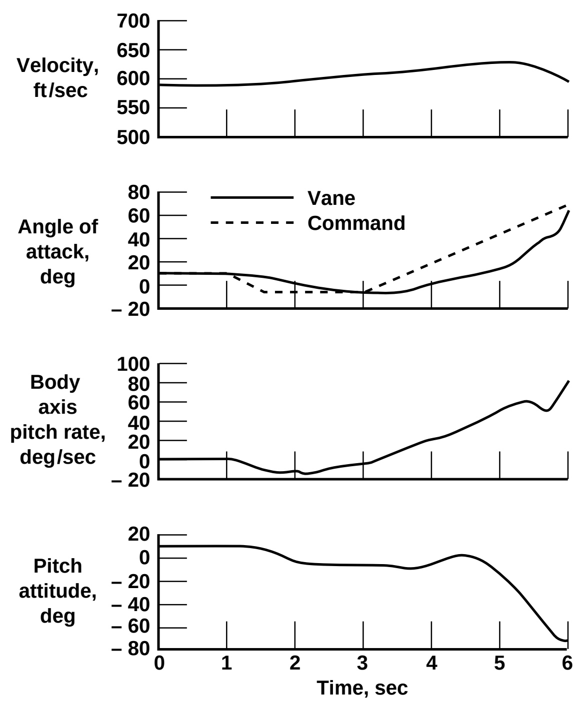


Figure 5. Longitudinal states from inertial coupling departure.

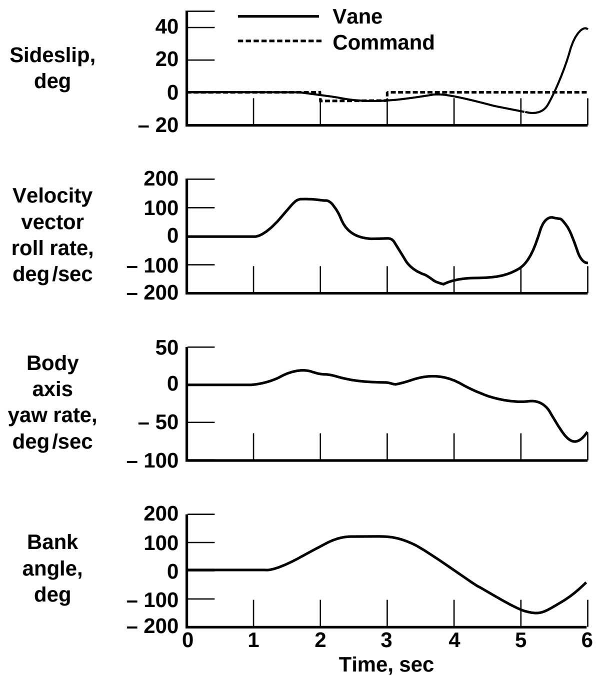


Figure 6. Lateral–directional states from inertial coupling departure.

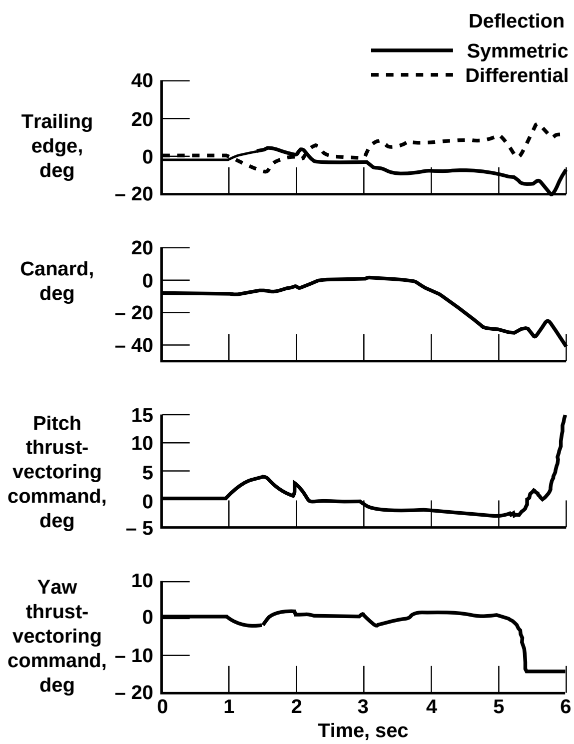


Figure 7. Control surface deflections from inertial coupling departure.

For the velocity vector roll to be coordinated, body axis yaw rate and roll rate must be related by the following expression:

$$r = p \tan \alpha \tag{4}$$

Otherwise, sideslip angle will build according to the following equation:

$$\dot{\beta} \cong p \sin \alpha - r \cos \alpha \tag{5}$$

Figure 8 shows that the change in sideslip rate, $\dot{\beta}$, builds up to a value above 120 deg/sec at the point where the departure occurs around 5 sec. The β sideslip indicates that roll and yaw rates are not coordinated, and that the flight control system is unable to achieve the desired zero-sideslip angle.

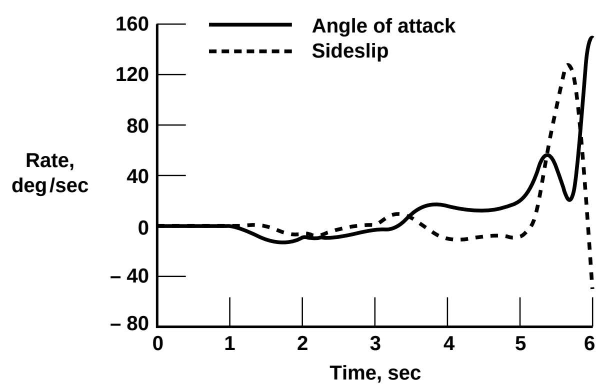


Figure 8. Angle-of-attack and sideslip rates from inertial coupling departure.

Inertial coupling departures have been well documented[17–21] and have led to restrictions in the number of consecutive rolls some modern fighters can perform. The X-31 aircraft was limited to one 360° roll at low angles of attack during its flight tests.* This departure mode indicates that the genetic search was able to locate a possible departure prone condition despite the fact that the X-31 flight control system was designed to compensate for inertial and gyroscopic coupling.[22]

* Bayati, J.E., "Temporary Operating Procedure for Rolling Performance," *Rockwell International Temporary Operations Procedure Manual for X-31*, TFD-90-1220L-15, Oct. 8, 1990. Contact the author for queries regarding this manual.

<u>Aerodynamic Asymmetry Departure</u>

Because inertial coupling departures are well known for modern fighters, further analysis was performed to see if the genetic search technique could find departure prone areas in the envelope caused by aerodynamic asymmetries. To this end, a lateral asymmetry similar to one found in flight testing of the X-31 aircraft[23] was added to the aerodynamic models of the simulation, and the genetic algorithm was allowed to search for departures.

Flight test data showed that an asymmetry existed on the X-31 aircraft with the worst values occurring at angles of attack from 60° to 70°. Figure 9 shows the ΔC_{no}, or change in yawing moment coefficient for zero sideslip, values as a function of angle of attack added into the X-31 aerodata tables. The values added are slightly different from those found in flight test, but the effects on the aircraft dynamics should be similar. These changes were added to the aerodata tables for the Mach 0.4 and Mach 0.2 breakpoints to test the ability of the genetic search technique to locate the specific portion of the flight envelope where the directional stability change was added. Also, the asymmetries from the nose vortices on the X-31 aircraft are more pronounced at low speeds. The same fitness function from the inertial coupling analysis was used for consistency.

Figure 10 shows the resulting inputs from the genetic search for this test case. The search converged on a trim

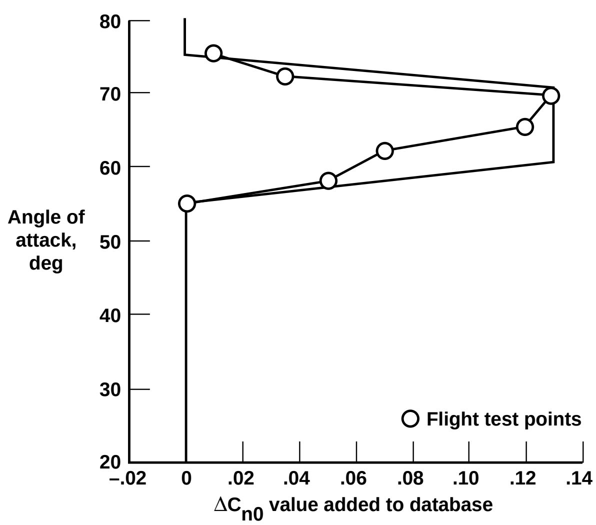
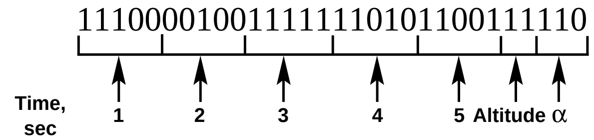
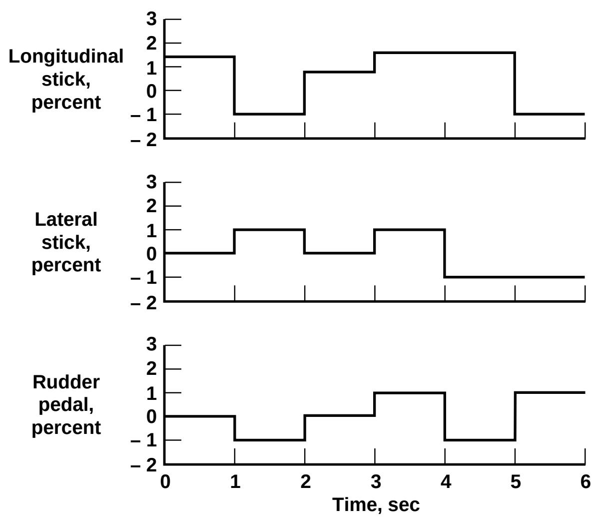


Figure 9. Change in yawing moment coefficient for zero sideslip values added to aerodynamic data.



(a) String representation of the control inputs. (Controls held at trim value from 0- to 1-sec point of run and held after last input.)



(b) Stick and rudder inputs.

Figure 10. Aerodynamic asymmetry departure inputs.

condition of 60° angle of attack at an altitude of 40,000 ft. Figures 11 and 12 show the resulting time history data from the departure. The departure occurs at a flight condition that corresponds to the Mach number and angle of attack where the asymmetry was added, which demonstrates the ability of the genetic search technique to locate specific areas of the envelope.

The inputs indicate that the simulation trims at a high angle of attack initially. At this high angle-of-attack condition, the asymmetry creates a yawing moment that is too great for the controls to overcome, indicated by the initial yaw rate build up after the start of the simulation.

Figure 13 shows that the yaw vectoring immediately saturates to try to overcome the directional instability. The flight control system tries to command the angle of attack to match the longitudinal stick input, taking the available control deflection from differential trailing edge and commanding full nosedown symmetric trailing-edge deflection. This pitch axis priority of the flight controls allows the yaw rate to increase to almost

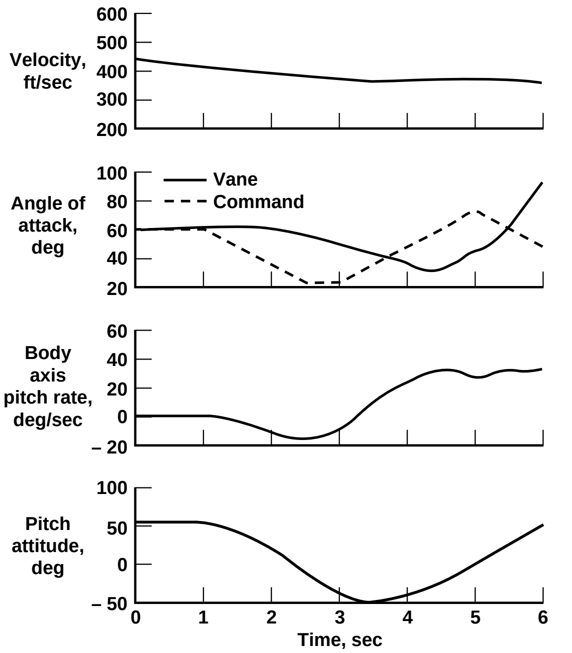


Figure 11. Longitudinal states from aerodynamic asymmetry departure.

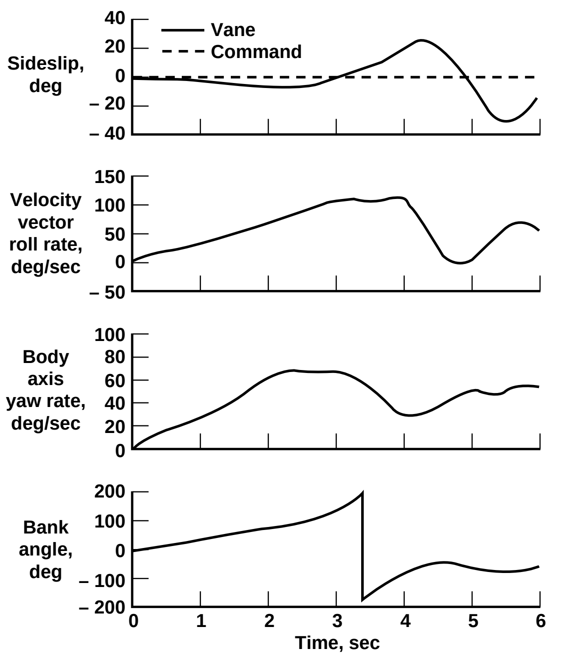


Figure 12. Lateral–directional states from aerodynamic asymmetry departure.

70 deg/sec after 2 sec. The asymmetry causes the proverse sideslip to increase to –10° which increases the roll rate to over 100 deg/sec after 3 sec. Again, inertial coupling between the roll and yaw rates results in an angle of attack increase to over 80° after 5 sec. The

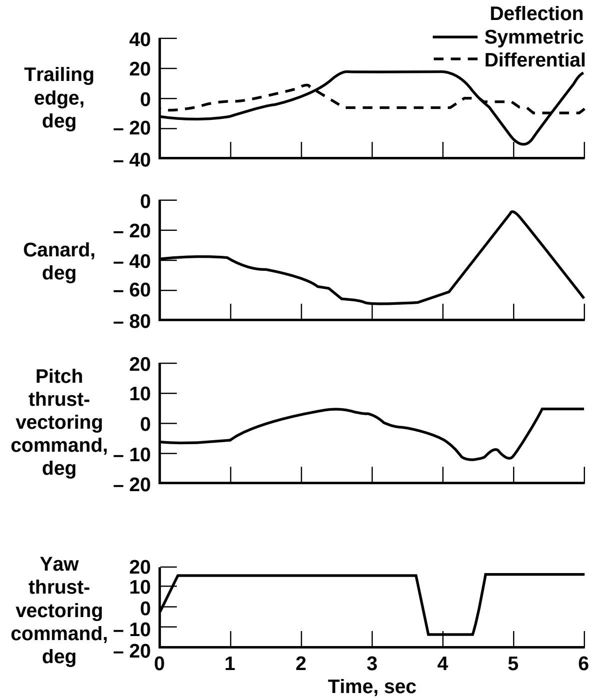


Figure 13. Control surface deflections from aerodynamic asymmetry departure.

sideslip time history also indicates that an unstable sideslip oscillation is occurring, with an increasing magnitude of over 30°. Values above 10° are considered over safe limits according to flight test procedures.

Figure 14 shows that the rate of angle of attack is again over the commanded maximum because of the departure. The change in sideslip also increases to over –70 deg/sec during the departure.

This simulated departure is similar to an in-flight departure of the X-31 aircraft during a 2-*g*, split-S to 60°

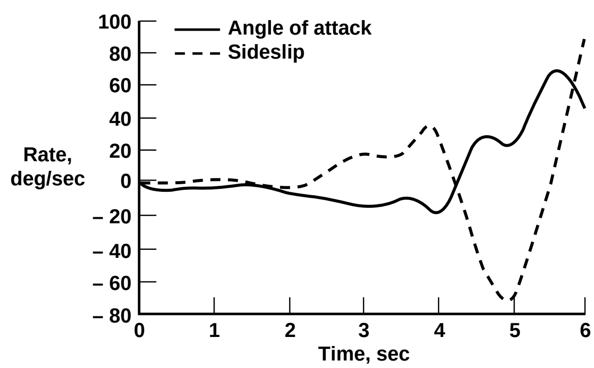


Figure 14. Angle-of-attack and sideslip rates from aerodynamic asymmetry departure.

angle of attack on flight 2-73. During this in-flight departure, the yaw-vectoring command was also position limited. In addition, the angle of attack increased to over 80°. Data from this in-flight departure showed that it was triggered by an unmodeled yawing moment similar to that added into the aerotables for this study.

If the same inputs are run through the simulation without the asymmetry modeled in the aerodata, the simulation did not depart. The maximum sideslip during the maneuver was 2°, and the maximum angle of attack was 60°, indicating that adding the asymmetry caused the inputs to lead to a departure. As a result, the genetic search technique demonstrated that it is possible to depart the aircraft simulation during highly dynamic maneuvers when these asymmetries are modeled.

Concluding Remarks

The departure modes found by the genetic search technique indicate that it can find input combinations that cause departures in different areas of the envelope. The following conclusions can be drawn from the results of this study:

1. Genetic search techniques offer an effective way to search for departure cases because the algorithm will run until it finds a departure. The analysis runs without the user having to guess at possible initial flight conditions that may be prone to departure.

2. Genetic search techniques can be very sensitive to the choice of the fitness function.

3. Departure conditions that may be overlooked by other departure prediction methods may be found using the quasi-random search techniques of genetic algorithms. Also, the method introduced here includes control system effects in the search.

The following recommendations are made as a result of this study:

1. Apply genetic search techniques to other high fidelity simulations to see if similar results are found.

2. Extend the technique developed in this study to see if it is applicable for system testing.

3. Study variations of total simulation time, input frequency, and control input magnitude to investigate changes in the results.

4. Study variations on the genetic algorithm parameters, such as crossover probability, mutation probability, and population size, to determine how the resulting departures differ.

5. Study other departures in the final population to determine if certain types of control input sequences are common between different flight conditions, indicating what types of inputs can lead to departures at several points in the envelope.

6. Study different fitness functions to find what other types of departures can be found. For example, the removal of roll rate from the fitness used may exclude inertial coupling departures from the final population.

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13. ABSTRACT (Maximum 200 words)

Methods of testing aircraft for departures range from simple, single-parameter criteria to complex, in-flight departure resistance maneuvers. These methods are useful for predicting departure characteristics, but single-parameter methods may be limited in accuracy because of simplifying assumptions made in their derivation. Also, in-flight or simulation testing of departure resistance maneuvers can be limited by the small number of conditions tested. These limitations increase at high angles of attack where the dynamics of the aircraft are more complex. This paper presents a method for using genetic algorithms to augment traditional evaluation criteria. Quasi-random control inputs are generated by a genetic algorithm for a high fidelity X-31 simulation. Each input is evaluated to determine if it causes a departure. The result of the genetic-algorithm-based search is a population, or set, of control input combinations that lead to uncontrolled flight conditions in the simulation. Recognizing possible differences and simplifications between simulation models and the real aircraft, the results show that the method used is effective for finding possible departures caused by inertial coupling and aerodynamic asymmetries. Simulation data are used to show the results of the genetic algorithm search.

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